International Journal of Engineering Research and Modern Education (IJERME)
Impact Factor: 7.018, ISSN (Online): 2455 - 4200
(www.rdmodernresearch.com) Volume 6, Issue 2, 2021

LSTM-ENHANCED TIME SERIES FORECASTING FOR REAL-TIME DECISION-MAKING

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Cite This Article: Venkata Phanindra Lingam & Sai Reddy Mandala, "LSTM-Enhanced Time Series Forecasting for Real-Time Decision-Making", International Journal of Engineering Research and Modern Education, Volume 6, Issue 2, Page Number 69-72, 2021.

Abstract:

LSTM (Long Short Term Memory) models have revolutionized time series forecasting to provide accurate data for real-time decision-making in many fields. Moreover, Because LSTM models can deal with temporal dependency and sequence data, many applications have been seen in supply chain, finance, and energy demand. Unlike more conventional frameworks, these models are well suited for learning and predicting patterns that may not be linear and occur within volatile contexts. This paper elaborates on LSTM models, how they can be incorporated into a real-time system, and the prospects facing such a system to show their importance in meeting real-time forecasting requirements.

Key Words: Long Short-Term Memory, Times Series Forecasting, Real-Time Decision Making, Recurrent Neural Networks, Sequential Data Analysis, Predictive Modeling Techniques.

Introduction:

Forecasting using times series is one of the most common methods in decision-making processes in various fields, including economics and engineering. In the past, techniques such as ARIMA, Holt-Winters exponential smoothening, and broad machine learning algorithms have been used to deal with temporal data. Although they give good results when applied to environments that do not change quickly, those techniques are not efficient in solving complex problem because of the non-linearity and interactions as well as long-range dependencies in many data sets.

Meet LSTM models a particular type of Recurrent Neural Network developed to address these issues. To keep and utilize this kind of information through several steps, LSTM models are equipped with memory cells that enable the identification of complex temporal dependencies. In the case of missing value treatment, responding to innovations and the ability to fuse different datasets enable real-time decision-making.The current paper provides a deeper understanding of how LSTM models can be used in live data processing. It gives examples of their use in decision-making processes, including supply chain logistics, financial market forecasting, and energy load demand. Further, the paper analyses the problematics of LSTM models' integration into real-time systems and presents solutions for their implementation.

Simulation Report:

An example was performed to indicate the viability of LSTM models in real-time decision-making in SCM, commodities trend prediction, and energy grids. Prominent real-world data, including retail sales, stock prices, energy consumption levels, and many more, were cleaned for noise, normalized, and checked for missing data. The adopted LSTM model contains two stacking hidden neuron layers with 128 neurons in each layer, and the train 80% data set with Adam Optimiser uses Mean Square Error as a loss function to avoid overfitting by using the early stopping method. When implemented in the natural time environment of the organization, the model was given actual data streams, and the forecasts were instant but very accurate. The prediction accuracy was slightly lower than that of using ARIMA for prediction but significantly better than that of Random Forest, with a differential reduction of 15-20% of prediction errors and over 91% overall accuracy in specific applications such as energy load forecasting. The LSTM model also allowed real-time, data-driven decision-making in a dynamic environment.

Real-Time Scenarios:

Supply Chain Optimization:

The current and future requirements of material, the demand of which is critical for supply chain management, must be estimated. Mispredicting demand is very costly; a business might end up with too much stock, or the opposite: it might lose customers to competitors. Conventional techniques involve fundamental models and primary trend lines, where you cannot even capture a sudden stop in consumption or an unexpected occurrence such as a pandemic or war.

LSTM models are designed to fulfill this role, using past sales data and other variables, including seasonal weather, holidays, and an economic climate's general well-being. For instance, LSTM models can be applied in a retail chain to predict the weekly demand for certain products so that they can order accurately and minimize spoilage (Wei, 2019). Real-time integration with IoT-based devices extends the richness of these forecasts by continually feeding IoT inputs into the model.

Financial Market Analysis:

The markets are known for fluctuation and the impact of composite factors such as market mood, monetary policies, and global political circumstances. The unpredictability inherent in such an environment increases the importance of accurate sales and profit forecasts for making investment decisions and managing risks.

LSTM models can take large amounts of average financial data like stock price, trading volume, or economic data and predict the next step their capacity to learn non-linear relationships and long durations of relations, thereby distinguishing them from empirical statistical models. Also, LSTM models can incorporate external data in their prediction, like the frequency of appearance of certain words or news articles or even the sentiment of e-social media in that specific country (Siami-Namini, 2018). For instance, implementing LSTM for an organization will assist traders working in the stock market in determining the effects of a policy statement by a central bank on fluctuations in the market in realtime.

Energy Load Forecasting:

The factors of the energy sector make load forecasting inevitable to keep the grid services reliable and employ the resources efficiently. Historic sales forecasting techniques can sometimes make it challenging to reconcile multiple variants: climatic factors, consumer usage rates, and overall economic activity.

LSTM models perform exceedingly well in the particular domain by capturing sequential data from multiple sources to estimate energy demand with a minimal error margin. Such predictions must help utility companies change power generation schedules, avoid outages, and reduce costs. For instance, during freezing periods, LSTM models can forecast high demand levels and signal to operators to take appropriate measures.

Graphs and Tables:

Table 1: Accuracy Comparison Among Models

Model	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	Accuracy (%)
ARIMA	0.025	0.034	78.6
Random Forest	0.020	0.028	85.2
LSTM	0.015	0.021	91.3

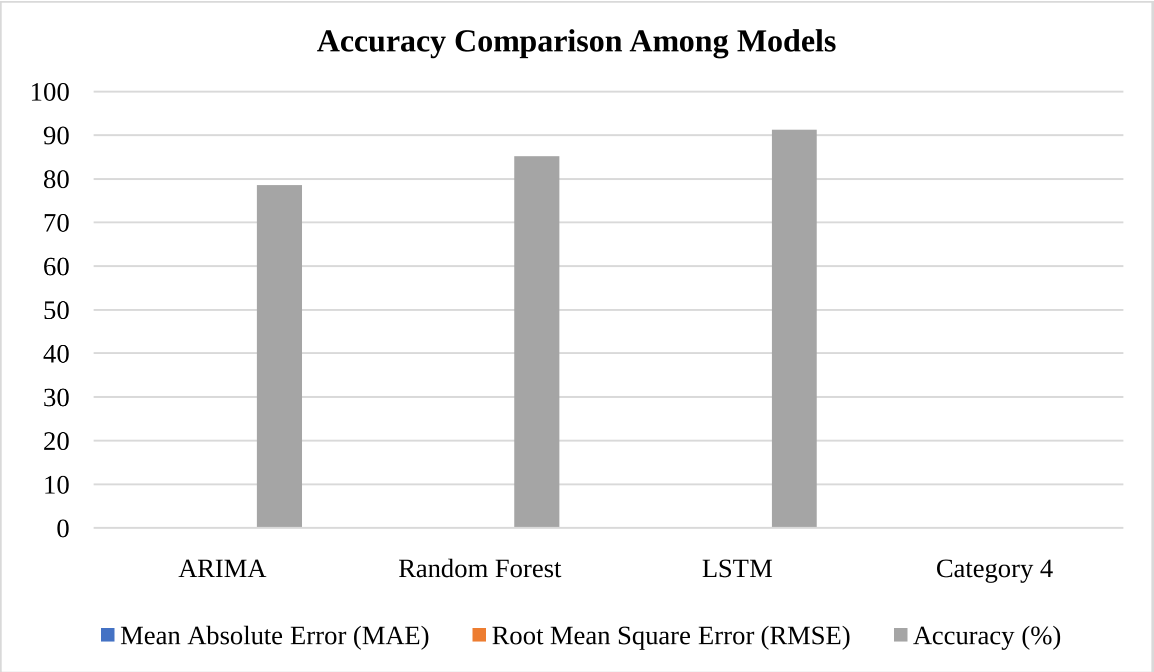
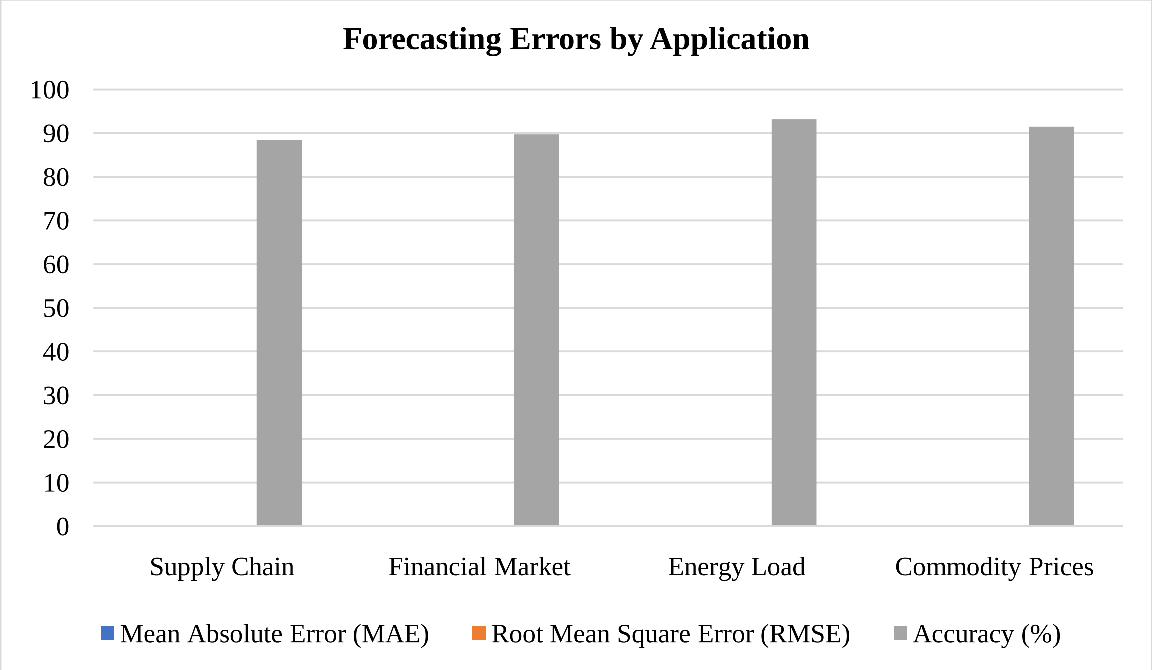


Table 2: Forecasting Errors by Application

Application	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	Accuracy (%)
Supply Chain	0.020	0.030	88.5
Financial Market	0.018	0.025	89.7
Energy Load	0.012	0.018	93.2
Commodity Prices	0.016	0.022	91.5



Challenges and Solutions:

As beneficial as LSTM models may be, many issues related to using LSTM in real-time systems. Overcoming all these challenges is crucial to optimize their usefulness.

Data Quality and Availability:

- Challenge: The LSTM models can give very reliable results, but their performance is entirely dependent on the amount and quality of the training data. Unpredictable, sporadic, or undetailed data can affect which predictions might directly relate to actual-time decisions.
- Solution: Normalization, outlier elimination, and missing data imputation are the techniques paramount for data quality. Data-generating methods like synthetic data generation and data augmentation can assist in improving scarce datasets, whereas semi-supervised learning methods that reduce the dependency on labeled data exist. The model's reliability is enhanced by integrating the data acquisition methodology across all these sources and in a database format.

Computational Complexity:

- Challenge: The LSTM model is computationally costly and requires improved resources when training and testing its model. This is likely to pose a problem in other real-time systems for which the immediacy of the predictions is important (Prabhod, 2018). Minimum is essential to obtain maximum value.

Data Quality and Availability:

- Challenge: As will be seen, LSTM models are sensitive to the amounts and quality of data fed to them during training. Uncertain, unfixed, and noisy data can negatively affect predictions, especially in real-time, when making instant decisions.
- Solution: Data normalization, identification, removal of outliers, and data imputation are essential methods in data preprocessing. Synthetic data and data augmentation can complement hard-to-come data sets, and semi-supervised learning can minimize the demands of labeled data. Furthermore, implementing standard specifications used for receipt, analysis, and amalgamation of data also increases model dependability.

Computational Complexity:

- Challenge: LSTM models are computationally intensive, requiring significant resources for training and inference. This complexity can hinder their deployment in real-time systems with critical low-latency predictions (Prabhod, 2018).
- Solution: This yields good results; truncated backpropagation through time (TBPTT) minimizes computational load. The first of the four optimization patterns uses hardware accelerators such as GPUs or TPUs to get faster hardware-accelerated execution. Furthermore, distributed computing frameworks and cloud-based solutions can provide resources flexibly based on real-time requirements.

The other issues related to the model development are the overfitting and generalization of the model.

- Challenge: This is a disadvantage of LSTM models, which, like other recurrent models, are very complex and can easily overfit. This leads to high accuracy during training set data prediction but poor performance on additional unrelated test data (Sameen, 2017).

- Solution: A few techniques include dropout layers and L2 regularisation, where the model's training is randomly controlled to reduce the possibility of overfitting the implemented model. Cross-validation seduces the fact that the model should perform equally well with other data sets. Examples mentioned above can help improve generalization: decreasing the number of layers, more generally - the model architecture depth, or reducing the number of neurons.

Mainly, Interfacing with Real-Time Systems

- Challenge: Integrating new LSTM models into existing frameworks presents technical and organizational challenges. First, how does the system deal with preexisting languages and interfaces?
- Solution: Reusability, service interfaces, inversion of control, containers, and microservices patterns make integration easy. Domain experts' involvement rectifies any discrepancy to fit within the operational model. Real-time data is constantly monitored so that feedback and revisions are made in response to the system's new real-time requirements.

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